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Model Calibration as a Tool for Leakage Identification in WDS: A Real Case Study

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Abstract

Water leakage detection is important for a proper management of water distribution systems (WDS). This paper proposes the application of the leak detection approach based on a new Bayesian calibration methodology. The methodology uses a new developed index μ, which takes into account the difference in roughness values in pipes of the calibrated models with and without leaks. The case study is referred to a real network and is presented to demonstrate how the approach can be used in identifying pipes with losses. The approach starts with the UNINET calibration method followed by the analysis of sensitivity matrices. The case study proves that the approach is effective in finding leaks in real networks, but the results depend on the quality of the observed data.

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Keywords: Model Calibration; Network Analysis; Water Pipe Networks; Leakage.

1. Introduction

Water loss by leaks is one of the major problems in water distribution systems (WDS). This problem causes consequence in terms of economic losses and water-quality issues. To provide a solution to the problem, the scientific community proposed some methodologies for leak detection and many papers on this topic have been published in recent years. Some modelling approaches are used for prediction of failures. These methodologies

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depend on the failure type, the complexity of the network and the availability and reliability of relevant data [1][2][3][4].

Today, pipe rehabilitation practice and theory have being actively developed, new materials for pipes are investigated and new factors influencing the probability of burst occurrences have being investigated. Authors generally develop a multi-objective strategy, and different algorithms have used for solving the task of planning optimisation and renovation. Some examples of these methodologies are: Genetic Algorithm by [5], a Fuzzy Rule based on non-homogeneous Markov process by [6][7], the Method of Cullinane by [8], Statistical Methods by [9], a Strength Pareto Evolutionary Algorithm (SPEA) by [10], or a Non-Sorting Genetic Algorithm II by [11]. In this context the detection of leaks is of high importance and methodologies of both prediction of pipe failures and detection of leaks are based on analysis of data of already detected leaks [12].

Currently, other methods for burst detection are appearing. This is due to the increase in computer power capable of providing fast information processed in large databases and connected to the availability of new numerical methods for WDS analysis. The burst finding pilot study using a calibration method proposed by [13] was successful and it proved that network models can be employed to identify system anomalies and areas of interest within the distribution network. There are other methods, which require continuous monitoring of the concerned area.

Puust et al. [14] proposed a methodology based on the Shuffled Complex Evolution Metropolis (SCEM-UA) algorithm which is capable of estimating the posterior probability density functions for unknown leak areas and their respective locations in an artificial network case-study. It seems that this approach is similar to the hybrid method presented in this report, but it has not been completely developed and unfortunately comparative analysis of these methods cannot be carried out. However, these models need sufficient time, efforts and resources to be fully realized, that is why the problem of water losses will remain important for the near future.

In any case, detection of a burst and location and identification of its size are not possible without system monitoring providing information about flow changes [15], and pressure changes [16]. The quality of collected information by monitors depends on the placement of pressure/flow loggers in the water distribution system.

To solve the problem of optimal placement of pressure/flow loggers some methods based on Genetic Algorithms (GA), Cluster Analysis and Regression Analysis were suggested. In this case an optimisation (search) method such as a Genetic Algorithm is used for the burst location, as suggested by [17]. Other methods are based on the use of sensitivity matrices, as [18]. The core of all these methods is in discovering sensitive nodes in the network, which can be assumed as representative of the behaviour of all other ones.

2. Calibration and methodology

In WDS the calibration methods are commonly used to obtain the value of roughness in pipes and demands at nodes. These parameters in fact are supposed known for the verification problem but are really unknown in calibration. All approaches to calibration can be subdivided into three different types of: 1) heuristic models, 2) explicit models and 3) implicit models. In this paper an implicit model is used to demonstrate that calibration methods can be used to find leaks in WDS.

The UNINET algorithm (Fig. 1), developed by [19], is used to calibrate roughness in pipes for some literature networks. The model uses the SCEM-UA methodology [20] as optimization algorithm and INetPDA, Veltri et al. (2010), as simulation model.

To estimate roughness in pipes and demands at nodes the model UNINET uses a Bayesian-statistical approach, which assumes the parameters as random variables. This approach solves the optimization and statistical analysis problems at the same time. The aim of this paper is the individuation of the area where a leak can be found. The methodology is based on the use of an index μ that measures the difference between the calibrated roughness in the i-th pipes before and after the introduction of a leak inside the network:

$$\mu_i = \frac{\left|\varepsilon_{cpi} - \varepsilon_{ci}\right|}{\varepsilon_{ci}} \tag{1}$$

where:

- μ_i is the value of the index μ for the i-th pipe;
- ε_{cpi} is the calibrated roughness, in mm, of the i-th pipe after the introduction of the leak in the i-th pipe of the WDS;
- ε_{ci} is the calibrated roughness, in mm, of the i-th pipe before the introduction of the leak in the WDS.

By this index it is possible to identify the area where the system anomalies, the leak in our case, are within the distribution network. For this kind of analysis pressure measures are more useful than flow ones and the choice of the nodes to use as known pressure data is made by the method of sensitivity matrices [21]. For the analyses the values of roughness in the pipes are calibrated starting from known measure data, first without a leak and then putting a leak in a pipe. The choice of the pipe affected by leak is random as the leak amount. After the calibration of roughness coefficient, the index μ is calculated and it is possible to individuate the area where the leak was put.

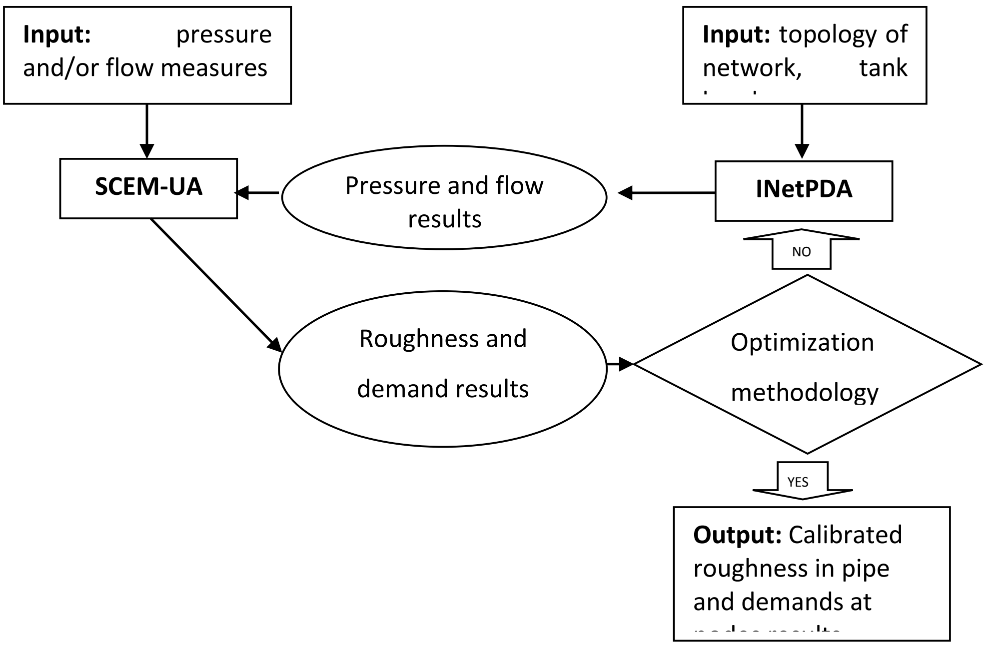

Fig. 1 - UNINET algorithm

A case study of the network of the city of Amantea (CS, Italy) is presented and this is a good starting point to show how the methodology can work in a real WDS.

3. Case study

The goal is to demonstrate that the methodology is useful to determine the area where a leak can be discovered in a real WDS. The analyses were made on the real network of the city of Amantea (CS, Italy).

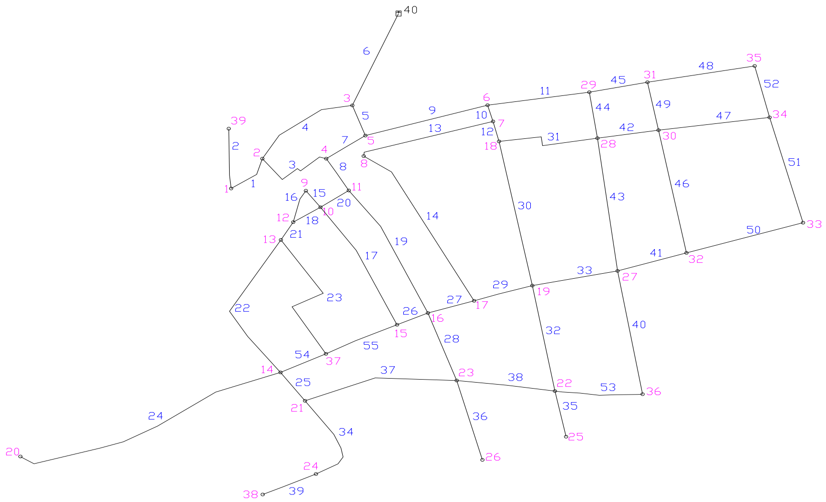

Fig. 2 - The Amantea WDS

The network (Fig. 2) consists of sixteen closed elementary mesh, one node of power, thirty-nine nodes of delivery and fifty-five pipelines [21]. For each analysis the values of roughness in the pipes were calibrated for different numbers of known measure data and with different locations of leak. In particular two different positions of leak were considered: the first in pipe 44, the second in pipe 55, with an amount of leak of 2.5% of total demand. Analyses were carried out using 9 classes of roughness, according to the age of pipe, as shown in the following table (Table 1).

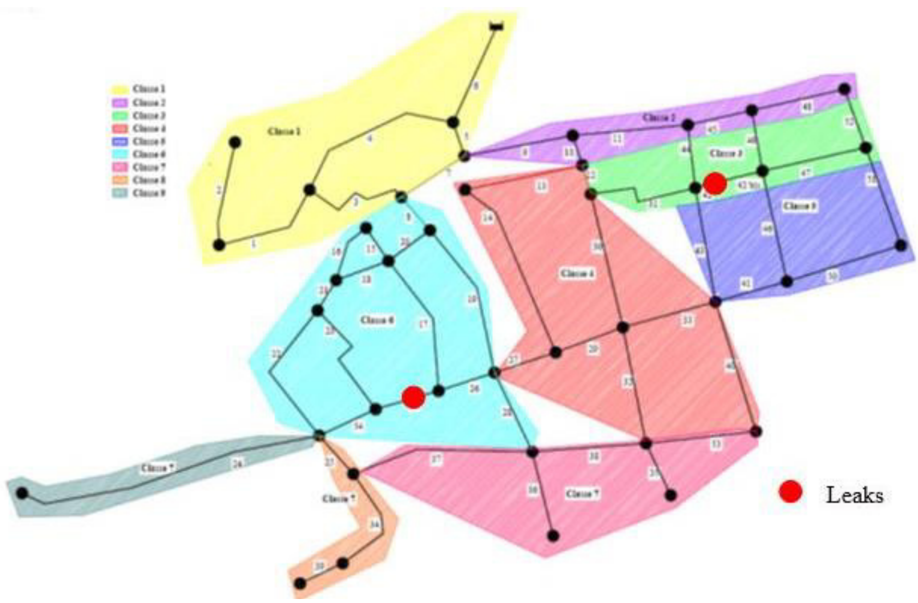

Fig. 3 - Roughness class of the network

Table1: Roughness classes assigned

Pipe ID	Roughness classes	Pipe ID	Roughness classes	Pipe ID	Roughness classes	Pipe ID	Roughness classes	Pipe ID	Roughness classes
1	1	12	3	23	6	34	8	45	2
2	1	13	4	24	9	35	7	46	5
3	1	14	4	25	8	36	7	47	3
4	1	15	6	26	6	37	7	48	2
5	1	16	6	27	4	38	7	49	3
6	1	17	6	28	6	39	8	50	5
7	1	18	6	29	4	40	4	51	5
8	6	19	6	30	4	41	5	52	3
9	2	20	6	31	3	42	3	53	7
10	2	21	6	32	4	43	5	54	6
11	2	22	6	33	4	44	3	55	6

The leak was positioned along the pipe 44 using a dummy node (Node 41) in which the value of leak was assigned as demand and then along the pipe 55 using another dummy node (Node 42) with the same condition. The results are shown in Table 2 and 3 and Fig. 4 and 5.

Table 2 - Results for the leak (0.87 l/s) in pipe 44: a) 1 known pressure data; b) 9 known pressure data; c) 10 known pressure data

Class ID	a)	ε_c	ε_{cp}	μ	b)	ε_c	ε_{cp}	μ	c)	ε_c	ε_{cp}	μ
1		0.041	0.0421	2.68%		0.4985	0.2971	40.40%		0.6076	0.7245	19.24%
2		0.1364	0.1545	13.27%		0.5324	0.5181	2.69%		0.6426	0.9454	47.12%
<u>3</u>		<u>0.4606</u>	<u>0.5998</u>	<u>30.22%</u>		<u>0.8549</u>	<u>1.1412</u>	<u>33.49%</u>		<u>0.8613</u>	<u>1.4089</u>	<u>63.58%</u>
4		0.2624	0.3247	23.74%		0.7368	0.9351	26.91%		0.7474	1.1452	53.22%
5		0.4933	0.6548	32.74%		0.8944	1.2854	43.72%		0.9733	1.3921	43.03%
6		0.1197	0.1432	19.63%		0.5438	0.5205	4.28%		0.6514	0.9423	44.66%
7		1.9461	1.8354	5.69%		1.2211	1.426	16.78%		1.292	1.5089	16.79%
8		0.6635	0.8721	31.44%		0.9816	1.2764	30.03%		0.9752	1.4725	50.99%
9		1.5153	1.498	1.14%		1.534	1.5037	1.98%		1.5556	1.4498	6.80%

Table 2 shows the results obtained for the network when nine roughness classes are used and the leak is along pipe 44. The class into which the leak is located has a high value of index μ. The roughness class 3, that is associated with pipe 44, has the highest percentage difference when one known data per class is used for analysis. Similar result is obtained when ten known data are used as shown in Fig. 4.

Table 3 shows the results obtained for the network when nine roughness classes are used and the leak is along pipe 55. The class into which the leak is located has a high value of index μ. The roughness class 6, that is associated with pipe 55, has the highest percentage difference when one known data per class is used for analyses. Similar result is obtained when ten known data are used as it is shown in Fig. 5.

The Figures above (Fig. 4-5) show what happens when the network is subdivided in nine roughness classes and the leak is inside the system. In particular the methodology allows to identify the position of leak in the roughness class with a high value of the index μ. This is true when a sufficient number of known data is used. In particular roughness class 3 and 6, that are associated with pipe 44 and 55, have the highest percentage difference when 9 or 10 known data measures are used to calibrate the roughness in pipes. According to the results, the methodology proposed is useful to check if a leak exists inside the system for real WDS and for the case study it is possible to identify where it is.

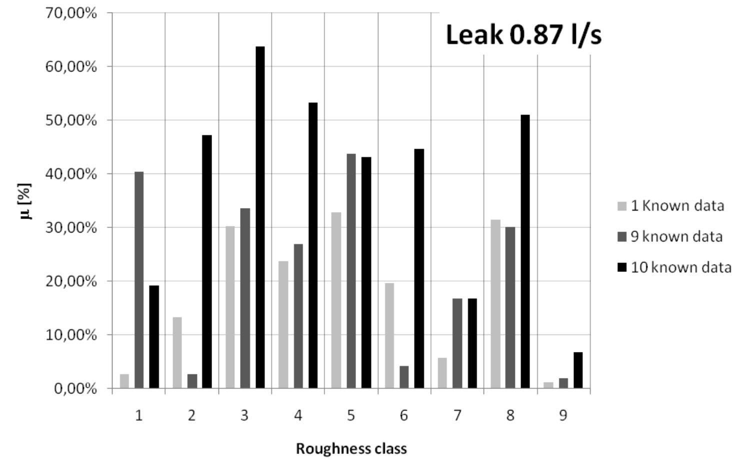

Fig. 4 - Results with 9 roughness classes and 0.87 l/s leak.

Table 3 - Results for the leak (0.87 l/s) in pipe 55: a) 1 known pressure data; b) 9 known pressure data; c) 10 known pressure data

Class ID	a)	ε_c	ε_{cp}	μ	b)	ε_c	ε_{cp}	μ	c)	ε_c	ε_{cp}	μ
1		0.041	0.0421	2.68%		0.4985	0.2538	49.09%		0.6076	0.4114	32.29%
2		0.1364	0.1545	13.27%		0.5324	0.4043	24.06%		0.6426	0.5551	13.62%
3		0.4606	0.5998	30.22%		0.8549	0.8497	0.61%		0.8613	0.8336	3.22%
4		0.2624	0.3247	23.74%		0.7368	0.6632	9.99%		0.7474	0.762	1.95%
5		0.4933	0.6548	32.74%		0.8944	0.8846	1.10%		0.9733	0.9153	5.96%
6		0.1197	0.1432	19.63%		0.5438	0.3969	27.01%		0.6514	0.5292	18.76%
7		1.9461	1.8354	5.69%		1.2211	1.3276	8.72%		1.292	1.2226	5.37%
8		0.6635	0.8721	31.44%		0.9816	0.8967	8.65%		0.9752	0.9714	0.39%
9		1.5153	1.498	1.14%		1.534	1.4417	6.02%		1.5556	1.5208	2.24%

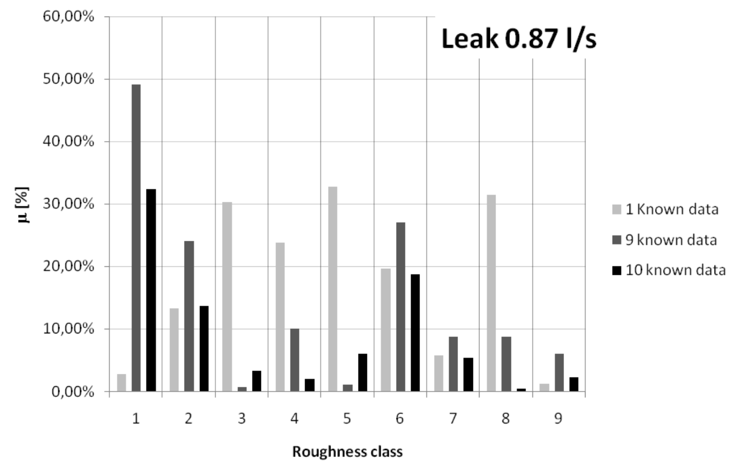

Fig. 4 - Results with 9 roughness classes and 0.87 l/s leak.

4. Conclusions

In this paper a methodology for the identification of the area where a leak can be found in a water distribution system has been presented. The methodology is based on a Bayesian calibration method and an index, μ.. This is done showing the variation of the calibrated roughness values in pipes. The methodology requires pressure measurement data at the locations, which are determined by using the sensitivity matrices method [22].The network analyses were carried out by using the UNINET simulation model. The leak localisation method was verified on the case study of the network of Amantea (CS, Italy).Different initial conditions were used to test the methodology. The satisfactory results show that the method can localise a leak without a high computational cost and significant errors, but it depends on the number and the quality of observed data.

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